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HOW COLLECTIVE IS COLLECTIVE EFFICACY? THE IMPORTANCE OF CONSENSUS IN JUDGMENTS ABOUT COMMUNITY COHESION AND WILLINGNESS TO INTERVENE*

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Existing studies have generally measured collective efficacy by combining survey respondents' ratings of their local area into an overall summary for each neighborhood. Naturally, this approach results in a substantive focus on the variation in average levels of collective efficacy between neighborhoods. In this article, we focus on the variation in consensus of collective efficacy judgments. To account for differential consensus among neighborhoods, we use a mixed-effects location-scale model, with variability in the consensus of judgments treated as an additional neighborhood-level random effect. Our results show that neighborhoods in London differ, not just in their average levels of collective efficacy but also in the extent to which residents agree with one another in their assessments. In accord with findings for U.S. cities, our results show that consensus in collective efficacy assessments is affected by the ethnic composition of neighborhoods. Additionally, we show that heterogeneity in collective efficacy assessments is consequential, with higher levels of criminal victimization, worry about crime, and risk avoidance behavior in areas where collective efficacy consensus is low.

Compelling evidence now exists that collective efficacy plays an important role in shaping the patterning of crime, disorder, and perceptions of victimization risk across local areas. Collective efficacy is conceived of as a confluence of networks, values, and norms of reciprocity that combine to enable individuals and communities to intervene as a way of suppressing norm-deviant behavior and of maintaining social order. Or, as

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Sampson put it, collective efficacy is “the process of activating or converting social ties among neighborhood residents in order to achieve collective goals, such as public order or control of crime” (2010: 802). Research findings across a range of contexts have shown that areas characterized by higher collective efficacy have lower levels of crime (e.g., Armstrong, Katz, and Schnellby, 2015; Mazerolle, Wickes, and McBroom, 2010; Oberwittler, 2007; Odgers et al., 2009; Sampson, 2012; Sampson and Wikström, 2007; Zhang, Messner, and Liu, 2007) and lower levels of fear of victimization and perceived disorder (e.g., Brunton-Smith, Sutherland, and Jackson, 2014; Farrall, Jackson, and Gray, 2009; Sampson, 2009). It has been posited as the social-psychological mechanism through which structural characteristics of local areas influence crime-related outcomes, mediating associations between neighborhood socioeconomic disadvantage and recorded and perceived crime rates (Morenoff, Sampson, and Raudenbush, 2001; Sampson, 2012; Sampson, Raudenbush, and Earls, 1997). Collective efficacy also seems to be important for understanding a range of other neighborhood-contingent social phenomena, including risky sexual behavior among teenagers (Browning et al., 2008), adolescent mental health (Browning et al., 2013), and confidence in the police (Nix et al., 2015).

Collective efficacy (henceforth CE) is considered to be an attribute of neighborhoods rather than of individuals: a combination of the networks, norms, and trust between residents and the capacity this endows them with to control and suppress anti-social and criminal behavior (Mazerolle, Wickes, and McBroom, 2010; Sampson, 2012; Zhang, Messner, and Liu, 2007). The collective and inherently subjective nature of the CE concept poses challenges for valid and robust measurement (Hipp, 2016). In existing empirical studies, scholars have predominantly approached these measurement challenges by eschewing “objective” indicators and, instead, have combined the subjective ratings of survey respondents into summary indicators (Raudenbush and Sampson, 1999). This has been done either by simple averaging (e.g., Bruinsma et al., 2013; Wells et al., 2006; Zhang, Messner, and Liu, 2007) or by using statistical modeling approaches that adjust for compositional differences between individuals and areas (e.g., Browning et al., 2008; Brunton-Smith, Sutherland, and Jackson, 2014; Sampson, Raudenbush, and Earls, 1997; Wikström et al., 2012). In these studies, researchers have focused on variation between neighborhoods in the *average* of CE assessments. They have asked whether higher or lower average levels of CE across neighborhoods is (conditionally) related to outcomes such as recorded crime, willingness to intervene, and perceptions of victimization risk. Considerably less attention has been paid to differences between neighborhoods in the *variability* of these assessments around their averages. Yet there are good reasons to believe that the level of consensus in residents’ assessments of CE will also differ across neighborhoods (Browning, Dirlam, and Boettner, 2016) and, moreover, that such differences will be consequential for individual and community responses to crime and norm-violating behavior (Downs and Rocke, 1979).

In this article, we consider CE from this perspective; we assess whether and how *variability* in CE assessments is related to crime-relevant outcomes within neighborhoods. Using data from a large random survey of London residents, we extend the standard two-level, mixed-effects model (multilevel model or hierarchical linear model) commonly employed in neighborhood effects research to a mixed-effects, location-scale model (Hedeker, Mermelstein, and Demirtas, 2008). This allows us to model the within-neighborhood heterogeneity in CE ratings as a function of characteristics of not just neighborhoods but also the individual raters themselves. In addition to

describing the patterning of CE consensus across and within neighborhoods, this also enables an assessment of whether and how this heterogeneity is itself constitutive of individual-level fear of crime, risk avoidance behavior, and the experience of violent victimization.

The remainder of the article is structured as follows. First, we review the existing literature on CE before setting out our theoretical expectations regarding the likely consequences of variability in CE judgments across neighborhoods. We then describe the data and measures on which our analysis is based and introduce the mixed-effects, location-scale model. After presenting the results of our analysis, we conclude with a consideration of the implications of our findings for understanding how levels of consensus in CE judgments shape the patterning of crime and risk perception across local areas.

COLLECTIVE EFFICACY: CENTRAL TENDENCY AND VARIANCE

CE is now firmly embedded in the lexicon of modern criminological theory and empirical research as an extension of classic theories of social disorganization (Park and Burgess, 1925; Shaw and McKay, 1942; Thomas and Znaniecki, 1927). Although questions remain about its status as a direct causal factor in promoting informal social control and preventing crime (Browning, 2009; Hipp and Wickes, 2017; Wickes et al., 2017) as well as its applicability in non-U.S. contexts (Sutherland, Brunton-Smith, and Jackson, 2013; Villarreal and Silva, 2006), it has nevertheless become a key construct for guiding research into the sociogeographic distribution of crime and disorder. First set out in Sampson and colleagues' pioneering research on the spatial patterning of crime in the city of Chicago (Morenoff, Sampson, and Raudenbush, 2001; Sampson, 2012; Sampson, Raudenbush, and Earls, 1997), CE has been proposed as the key social-psychological factor to account for why some neighborhoods with predisposing structural characteristics—socioeconomic disadvantage, residential mobility, and ethnic heterogeneity—experience high levels of crime, whereas others do not. In these and subsequent studies (Mazerolle, Wickes and McBroom, 2010; Odgers et al., 2009; Zhang, Messner, and Liu, 2007), scholars have found that socially cohesive neighborhoods are characterized by cross-cutting social networks and high levels of interpersonal trust, combined with a willingness of residents to intervene to prevent norm-deviant behavior. In drawing on Bandura's (1997) theory of self-efficacy, Sampson, in his notion of CE, emphasized residents' shared expectations about the beliefs and likely actions of others, viewing this as underpinning a community's "latent capacity for action" (2013: 20). From this perspective, it is residents' *beliefs* about the likely behavior of others and not simply the objective level of informal social control, or signs of disorder in the neighborhood, that are key to shaping community responses and, therefore, to maintaining order.

Sampson and colleagues, in their original research, assessed how CE assessments are related to sociodemographic characteristics of neighborhood residents (Sampson, Raudenbush, and Earls, 1997). The results of subsequent studies have shown that residents' interpretations of the sorts of neighborhood structural properties that influence CE assessments are shaped by subjectivities and local context. Here, the focus has been on understanding the ways in which individual- and neighborhood-level characteristics are related to residents' interpretations of potential signs of disorder. For example, Sampson

(2009) has shown that the same signifiers—an abandoned car, graffiti, a broken window—are viewed differently, depending on residents' beliefs about the ethnic composition and social status of an area (see also Sampson, 2012; Sampson and Raudenbush, 2004). An abandoned car in a predominantly White, middle-class area does not induce crime-related cognitive schema to the same extent that it does in a predominantly Black, working-class neighborhood. Thus, Sampson (2013: 17) argued that “norms about order are inherently cognitive and contextual, conditioning responses to what are presumed to be objective markers of disorder.” Similarly, Hipp (2010) showed that Whites, women, parents, and longer term residents perceive higher levels of crime and disorder than do other demographic groups (see also Sampson, 2012), whereas in the United Kingdom, Sutherland, Brunton-Smith, and Jackson (2013) found higher ratings of CE among older people, ethnic minorities, and longer term residents.

In existing studies, then, scholars have identified a range of factors that seem to influence perceptions of the level of CE in a neighborhood and have described how variation in levels of CE across spatial contexts is associated with recorded crime and the individual and collective action propensities of residents. Considerably less attention has been paid, however, to the potential importance of heterogeneity in these judgments between residents of the same neighborhood. There are good *prima facie* grounds, though, to anticipate that the level of CE consensus will vary across local areas. This is because providing judgments about the likely actions of others is difficult, requiring as it does, quantitative assessments of the beliefs, attitudes, and behaviors of a vaguely defined set of actors in a broad range of contexts (Hipp, 2016). The amount and quality of information on which to base such judgments, as well as an individual's levels of exposure to relevant information, will vary across neighborhoods and, in many instances, will be sparse. When information about the local area is limited, there is increasing scope for people to interpret the same information differently, either basing their judgments on assessments of their own capacity to intervene (Reynald, 2010), their experiential knowledge of the environment (Hipp, 2016; Lippold et al., 2014), or relying on cognitive shortcuts and heuristics (Tversky and Kahneman, 1974).

In addition to interpreting the same informational cues in different ways, a key additional source of CE disagreement is likely to result from residents drawing on idiosyncratic neighborhood definitions. In most quantitative studies, researchers implicitly assume a shared understanding of neighborhood boundaries between residents, typically approximated by administrative units such as blocks, block groups, census tracts, or zip codes. In practice, however, residents of such well-defined areal units will have heterogeneous conceptions of what constitutes their actual neighborhood (Chaskin, 1997; Haney and Knowles, 1978). From this more psychological perspective, neighborhoods are better characterized as fuzzy and overlapping “ego-hoods” than as well-defined geographical units with clearly defined and consensually understood boundaries (Hipp and Boessen, 2013; Sampson, 2002). In short, variability in CE consensus between neighborhoods will result both from differences in evaluations of the same cues and from differences in the cues and signals being evaluated.

We noted earlier that few existing studies have focused on the variability, as opposed to average ratings, of CE. An exception is the work of Browning, Dirlam, and Boettner (2016), who sought to integrate the apparently conflicting effects of ethnic heterogeneity on both social disorganization and “immigrant revitalization” to explain variability in CE consensus between local areas in Chicago and Los Angeles. In a large body of research,

emanating most notably from Robert Putnam (2007), scholars have contended that, in the short term at least, ethnic heterogeneity reduces interpersonal trust, fragments social networks, and weakens attachment to norms of prosocial behavior (Alesina and La Ferrara, 2000, 2002; Costa and Kahn, 2003; Delhey and Newton, 2005). By way of contrast, immigrant revitalization perspectives emphasize the social ties, local support networks, and culturally oriented organizations that characterize many immigrant communities, and which produce and reinforce place-based attachments and interpersonal trust (Browning and Soller, 2014; Kubrin and Desmond, 2015). Browning and colleagues contended that which of these two processes dominates in local areas depends on the size of the immigrant population; low levels of immigrant concentration result in social disorganization, but as the proportion of immigrants in a neighborhood increases beyond a critical threshold, processes of community revitalization come to dominate.

This nonlinearity, Browning, Dirlam, and Boettner (2016) argued, arises as a result of changes in the “neighborhood narrative frames” of recently arrived immigrants as their own ethnic share of the resident population increases over time. Neighborhood narrative frames comprise a complex of preexisting cultural schema; levels of involvement in community activities, strength of social networks, and knowledge about the actions of residents, which render particular features of the local environment especially resonant for different groups (Small, 2004). For instance, even though a local community center may act as an important signifier of the potential for informal social control among long-term residents, it is unlikely to serve the same function for recent arrivals, who lack the shared community understanding of its role and functions. Frame convergence results from, *inter alia*, growth in the number of local amenities such as shops, community centers, sports clubs, and so on, which are targeted at the immigrant group. Thus, as immigrant concentration increases, the neighborhood comes increasingly to be defined by all residents as diverse and co-ethnic, leading to more widely shared understandings of the community’s capacity to intervene and control deviant behavior. In both Chicago and Los Angeles, Browning and colleagues found support for this expectation, observing a U-shaped curvilinear association between the concentration of Latinos and the levels of CE consensus within neighborhoods; when Latino concentration was low, CE consensus decreased as the Latino share increased. Once the Latino share reached a threshold of approximately 40 percent, however, further increases in Latino concentration resulted in *higher* CE consensus.

Although our primary focus in this article is on the *consequences* rather than on the causes of CE consensus, we begin our empirical analysis with an assessment of whether the same nonlinearity generalizes to London, a city with a different history of immigration, ethnic composition, and racial politics compared with American conurbations. London has a large and growing immigrant population, with slightly more than a third of inhabitants being foreign-born in 2015 (Rienzo and Vargas-Silva, 2017). The largest immigrant communities in London originate from former British colonies in the Caribbean, Nigeria, India, Pakistan, and Bangladesh, as well as more recently from Eastern Europe (Greater London Authority, 2013). Ethnic minority groups in the United Kingdom have experienced higher levels of social and economic disadvantage compared with Whites, with poorer educational and employment outcomes (Runnymede Trust, 2000; Weekes-Bernard, 2007), and higher rates of arrest and criminal conviction (Ministry of Justice, 2011). Nonetheless, ethnically diverse communities in London are also associated with urban renewal and civic vitality (Hall, 2011; Johnson, 2009) and have been shown to

express higher levels of social cohesion compared with more homogenous and segregated parts of the city (Sturgis et al., 2014). London, therefore, serves as a useful test bed for assessing the generality of Browning, Dirlam, and Boettner's (2016) conclusions regarding the U-shaped relationship between immigrant concentration and CE consensus to urban environments outside the United States.

CONSEQUENCES OF COLLECTIVE EFFICACY CONSENSUS

It seems likely that an inability to agree among neighborhood residents on their collective inclination and capacity to exert formal and informal social control will militate against the mooted beneficial effects of higher average levels of CE. As Browning, Dirlam, and Boettner noted, "higher levels of collective efficacy may not translate into coordinated action on behalf of communities if also accompanied by substantial disagreement" (2016: 800). Our theoretical expectation here turns on the importance of "theory of mind" in Sampson's account of CE, "a key argument of collective efficacy theory is that it matters *what I think others think*, making collective efficacy a kind of deterrence or moral rule—a generalized mechanism of 'common knowledge' that goes beyond any single act of control" (2013: 20). Thus, insofar as residents' expectations about the beliefs and likely actions of others are central to determining whether a community has the capacity to act, latent social control processes will be less readily translated into collective action in neighborhoods where CE consensus is low.

Findings from studies in the tradition of routine activity theory (Cohen and Felson, 1979; Felson, 2006) have demonstrated the central role of guardianship and the key function of knowledge and information about local context among guardians, in determining victimization risk in a range of contexts (Garofolo and Clarke, 1992; Miethe and Meier, 1990; Rountree, Land, and Miethe, 1994). Lack of agreement about the level of CE is, we contend, likely to inhibit the availability of "capable guardians" willing to intervene in local areas, which in turn serves to facilitate victimization by motivated offenders as they come together in time and space with suitable targets (Felson, 2006). As Reynald put it, "the more knowledge and experience residential guardians have with their context, about crime and about self-protective behaviors, the more confident they will be about their capability, and the greater their willingness to intervene" (2011: 119). In essence, then, where the signs and signifiers of local interpersonal trust, social cohesion, and willingness to intervene are "noisy," the protective effects of CE in a local area will be diminished and, by the same token, will be accentuated in areas where the CE "signal" is stronger (Jackson, 2006). These expectations lead to our first hypothesis:

Hypothesis 1 (H1): The negative association between (higher) average levels of CE and individual-level worry about victimization within local areas is stronger at higher levels of CE consensus.

If a lack of consensus about the level of CE in a neighborhood inhibits its ability to support collective action and reduces residents' concerns about the risk of victimization, we should expect low levels of CE consensus to affect behavioral as well as psychological outcomes. For example, it should result in residents deliberately avoiding locations and situations where they believe they are more likely to be subject to antisocial behavior or to be a victim of crime. This leads to our second hypothesis:

Hypothesis 2 (H2): The negative association between (higher) average levels of CE and crime-related risk avoidance behavior within local areas is stronger at higher levels of CE consensus.

Our third hypothesis relates to actual victimization experiences. If neighborhood residents do not expect others to provide support when they are deciding whether to intervene in threatening situations, the deterrent benefits of guardianship and “eyes on the street” will be less readily translated into effective social control (Jacobs, 1961). Thus, in contexts where residents cannot reliably assess the degree of CE in their local area, the availability of capable guardians and their willingness to intervene will be reduced, resulting in more encounters between motivated offenders and unprotected targets. Our third hypothesis is therefore:

Hypothesis 3 (H3): The negative association between (higher) average levels of CE and individual experiences of victimization within local areas is stronger at higher levels of CE consensus.

DATA AND MEASURES

Our data are drawn from the U.K. Metropolitan Police Public Attitude Survey (METPAS), a face-to-face survey of London residents 15 years of age and older. METPAS was initially established to inform policing priorities in London, but it has increasingly been used to provide in-depth information on the experiences of London residents (see, e.g., Bradford, Jackson, and Stanko, 2009; Jackson et al., 2012; Sturgis et al., 2014). It has a multistage sample design, with households randomly selected from the Post Office Address File within each of London’s 32 boroughs each quarter.¹ We use the April 2007 to March 2010 rounds of the survey, with a response rate over the 3 years of 60 percent (Cello, 2009). This is comparable to the response rate of other large-scale social surveys, and comparisons with the 2001 U.K. national census reveal that the sample is broadly representative of the population of London, with a slight underrepresentation of young (aged 15–34) White residents (Cello, 2009).

We use the Middle Layer Super Output Area (MSOA) census geography (Martin, 2001) to represent neighborhoods. MSOAs are broadly equivalent to U.S. census tracts and provide an approximation to a plausible neighborhood geography, comprising an average of 4,000 households that are grouped together based on similarity of housing tenure, with an average size of .6 square miles. During the construction of MSOAs, consideration was given to the presence of major roadways and other physical barriers within the environment that may signify the boundary of a neighborhood area for residents. Data are available for a total of 46,346 residents within 982 MSOAs across London (an average of 47 sampled residents in each area).

1. The City of London was not included in the METPAS sample frame as it is not under the jurisdiction of the Metropolitan Police force. London is atypical, acting primarily as a business and financial center with a very low resident population (approximately 7,000) but a very high day-time population (approximately 300,000).

COLLECTIVE EFFICACY

Collective efficacy is measured using six items tapping different aspects of social cohesion and informal social control, which closely mirror the questions used by Sampson, Raudenbush, and Earls (1997). For each item, respondents rated their local area on a five-point Likert scale from strongly disagree (1) to strongly agree (5):

1. People in this neighborhood can be trusted.
2. People act with courtesy to each other in public spaces in this area.
3. You can see from the public space here that people take pride in their environment.
4. If any of the children or young people around here are causing trouble, local people will tell them off.
5. The people who live here can be relied upon to call the police if someone is acting suspiciously.
6. If I sensed trouble whilst in this area, I could get help from people who live here.

Responses to all six items were combined using exploratory factor analysis (EFA).² A single factor with an eigenvalue greater than 1 was extracted, representing the overall rating of neighborhood collective efficacy for each individual (details of the factor model and parameter estimates are included in table A1 in the appendix). Higher scores on the factor score correspond to assessments of higher collective efficacy.

WORRY ABOUT VICTIMIZATION

Worry about victimization is measured using four items. Respondents were asked how worried they were about *having your home broken into and something stolen, being mugged or robbed in this area, being insulted or pestered by anybody whilst in the street, and being physically attacked by a stranger in the street in this area*. For each item, the response alternatives were “not at all worried,” “not very worried,” “fairly worried,” and “very worried.” EFA was used to combine the scores from each item, with factors retained if they had an eigenvalue greater than 1. This identified a single summary scale, with higher scores indicating more worry about crime overall (factor loadings included in table A1 in the appendix).

RISK AVOIDANCE BEHAVIOR

Respondents were asked three questions about their risk avoidance behavior: *How often do you do these things in your local area, simply as a precaution against crime – i) avoid using public transport, ii) avoid particular streets during the day, and iii) avoid particular streets at night* (never = 0, occasionally = 1, sometimes = 2, most of the time = 3, always = 4). These items were combined into a single count variable from 0 to 12, where 0 identifies those respondents who had never taken any precautionary measures against crime and 12 identifies those that responded “always” to all three items.

2. Like the IRT model used by Sampson and colleagues (Sampson, Raudenbush, and Earls, 1997; Raudenbush and Sampson, 1999), this makes adjustments for measurement error in the individual items. We adopt a two-stage approach to enable inclusion of our CE ratings within the location-scale model specification.

VIOLENT VICTIMIZATION

We use a binary indicator that records whether the respondent reported being a victim of any violent crime in the local area during the previous 12 months. Respondents first reported whether they had been a victim of crime, with a follow-up question requiring them to state whether this was violent, property related, or other. We focus here on violent crime because these offenses have been more frequently shown to be affected by collective efficacy (Armstrong, Katz, and Schnelby, 2015; Sampson, Raudenbush, and Earls, 1997; Wikström et al., 2012). These questions were only included in the final year of data collection (April 2009–March 2010), reducing the analytic sample to 16,021.

NEIGHBORHOOD CHARACTERISTICS

We link variables from the 2001 U.K. census to MSOAs to control for structural characteristics of local areas. A total of 21 raw census count variables were combined using a factorial ecology model (Rees, 1971), with a total of five neighborhood indices extracted (details of the full factor structure are included in table A2 in the appendix). These measures cover the extent of *concentrated disadvantage* (areas with a higher number of single parent families, those on income support and unemployed, fewer people in managerial and professional occupations, and less owner occupiers), *urbanicity* (high population density and domestic properties and little green space), and *population mobility* (higher levels of in- and out-migration and more single-person households). We also account for differences in the neighborhood *age structure* (with higher scores for areas with a younger population), and *housing structure* (higher scores for areas with more terraced and vacant properties). The sample size in each neighborhood is also recorded. The *ethnic composition* of the local area is measured by the percentage share of each ethnic group (Asian, Black, Other) in each MSOA, as well as by a quadratic term to allow for nonlinearity.

INDIVIDUAL CHARACTERISTICS

To account for differences in fear of crime, risk avoidance, and victimization that have been identified in existing literature (for reviews, see Hale, 1996; Pratt and Cullen, 2005; Rubin, Gallo, and Coutts, 2008) and that might otherwise be attributed to our theoretical predictors of interest, we include individual-level controls for gender, age, ethnicity, marital status, social class, housing tenure, and work status.

MODELING STRATEGY

We use a mixed-effects, location-scale model (Hedeker, Mermelstein, and Demirtas, 2008). This extends the standard two-level, mixed-effects model by relaxing the assumption of a common level 1 variance, instead allowing it to vary randomly across level 2 units and as a function of covariates. Whereas Hedeker et al. proposed their model in the context of analyzing intensive longitudinal data, it has since also been applied to cross-sectional settings (Brunton-Smith, Sturgis, and Leckie, 2017; Leckie et al., 2014). In the present case, we have individuals at level 1 within neighborhoods at level 2, and so it is the within-neighborhood (between individual) variance in CE assessments that we allow to vary from neighborhood to neighborhood, in addition to the usual mean differences.

Let y_{ij} denote the continuous CE assessment score derived from our EFA for individual i ($i = 1, \dots, n_j$) living in neighborhood j ($j = 1, \dots, J$). The standard two-level,

random-intercept, mixed-effect model for y_{ij} to derive covariate adjusted mean CE estimates for each neighborhood can then be written as:

$$y_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta} + u_j + e_{ij} \quad (1)$$

where \mathbf{x}_{ij} is a vector of individual- and area-level covariates with coefficient vector $\boldsymbol{\beta}$, u_j is a random intercept representing unobserved influences common to all individuals in neighborhood j , and e_{ij} is the residual. The random effect and residual are assumed independent of one another and of the covariates and to be normally distributed with zero means and constant variances, $u_j \sim N(0, \sigma_u^2)$, and $e_{ij} \sim N(0, \sigma_e^2)$. The between-neighborhood random effect variance σ_u^2 captures the variability in covariate adjusted mean levels of CE across neighborhoods and can be used to derive (reliability adjusted) posterior estimates, \hat{u}_j , for each neighborhood. The within-neighborhood or residual variance σ_e^2 measures the average variability in residents' CE assessments that are unexplained by the model. Including individual- and neighborhood-level covariates enables examination of systematic differences in individual assessments of CE between individuals with different characteristics, and how mean CE differs across neighborhoods after controlling for neighborhood differences in the compositions of individuals.

The degree of residual clustering in the data is typically then assessed by the intraclass correlation coefficient (ICC), derived as $\rho = \sigma_u^2 / (\sigma_u^2 + \sigma_e^2)$ and interpreted both as the proportion of unexplained variation that lies between neighborhoods and as the correlation in adjusted responses between two randomly selected residents in the same neighborhood. The ICC can therefore be used as a measure of consensus in assessments of CE among residents in the same area, with a higher ICC indicating greater consensus.

To examine how the degree of consensus in CE ratings differs across neighborhoods, we relax the assumption of a constant within-neighborhood variance, which is to say that although σ_e^2 is constrained to be equal across all neighborhoods in equation 1, the mixed-effects, location-scale model relaxes this assumption by specifying an auxiliary log-linear equation for this variance as a function of covariates and as an additional neighborhood random effect. This allows neighborhoods to differ in the residual variability (i.e., the degree of between resident agreement in CE ratings) once direct effects on the mean have been accounted for. The log link function ensures the within-neighborhood variance takes positive values. It is written as:

$$\ln(\sigma_{e_{ij}}^2) = \mathbf{w}'_{ij}\boldsymbol{\alpha} + u_j^{[2]} \quad (2)$$

where $\ln(\sigma_{e_{ij}}^2)$ is the log of the now heterogeneous within-neighborhood variance, \mathbf{w}_{ij} is a vector of individual- and neighborhood-level covariates with coefficient vector $\boldsymbol{\alpha}$, and $u_j^{[2]}$ is the additional neighborhood random effect. We use the “[2]” superscript to distinguish this random effect from the usual neighborhood random effect in equation 1, which we now denote $u_j^{[1]}$. Positive coefficients in $\boldsymbol{\alpha}$ identify individual and neighborhood characteristics associated with more variable CE assessments, whereas negative coefficients identify individual and neighborhood characteristics associated with less variable CE assessments.

In the terminology of the mixed-effects, location-scale model, the $u_j^{[1]}$ are “location” (i.e., mean) random effects, whereas the $u_j^{[2]}$ are “scale” (i.e., variance) random effects.

The two sets of neighborhood random effects are assumed bivariate normally distributed with zero mean vector and constant variance–covariance matrix:

$$\begin{pmatrix} u_j^{[1]} \\ u_j^{[2]} \end{pmatrix} \sim N \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u[1]}^2 & \\ \sigma_{u[1]u[2]} & \sigma_{u[2]}^2 \end{pmatrix} \right\} \quad (3)$$

The variance–covariance matrix summarizes how neighborhoods differ in average levels of CE (summarized by $\sigma_{u[1]}^2$) and in the variability of their residents' CE assessments (summarized by $\sigma_{u[2]}^2$). The association between the mean and variance random effects ($\sigma_{u[1]u[2]}$) can also be estimated.³ This can then be used to derive posterior estimates of the neighborhood-specific CE variance random effects, $\hat{u}_j^{[2]}$, in addition to the neighborhood mean CE random effects, now $\hat{u}_j^{[1]}$.

By specifying heterogeneous within-neighborhood variances, it follows that the ICC now also varies across neighborhoods and as a function of the covariates, allowing analysis of the heterogeneity in neighborhood agreement in CE ratings. The usual population-averaged ICC yielded by the standard mixed-effects model is recovered by first calculating the population-averaged within-neighborhood variance:

$$E(\sigma_{e_{ij}}^2 | \mathbf{w}_{ij}) = \exp(\mathbf{w}_{ij}'\boldsymbol{\alpha} + 0.5\sigma_{u[2]}^2) \quad (4)$$

and then substituting this for the level 1 variance in the expression for the ICC.

To test hypotheses H1 to H3, conventional two-level, mixed-effects models (equivalent to equation 1) are fitted separately to the three individual outcome variables: worry about victimization, risk avoidance behavior, and violent victimization experience. The (reliability adjusted) posterior estimates of the location and scale random effects $\hat{u}_j^{[1]}$ and $\hat{u}_j^{[2]}$ derived from equation 3 are included as predictors, as well as the interaction between these two sets of predicted random effects to allow consensus to moderate the effect of mean CE on each outcome. To ensure that effects of the measure of neighborhood CE consensus are not the result of differences in the levels of outcome variable for those that depart the most from the neighborhood mean CE, we also control for individual CE ratings.

ANALYSIS

Model 1 is a mixed-effects, location-scale model with no covariates, which allows the within-neighborhood variance in CE ratings to vary across areas in addition to the usual partitioning of the total variability in CE ratings into within- and between-neighborhood variance components. Significant variation in the within-neighborhood variance across local areas implies that residents of different neighborhoods vary in their level of CE consensus. Model 2 incorporates the individual- and area-level covariates and the measures

3. A nonlinear association between the mean and the variance is also permissible, allowing for the fact that the variability of CE assessments may be lower in neighborhoods with very high or low average estimates of CE (Hedeker and Nordgren, 2013; Leckie, 2014). An examination of the residuals, however, suggested a linear covariance was sufficient in the current analysis.

Table 1. Model 1: Mixed-Effects, Location-Scale Model With No Covariates

Variables	Mean	(SD)	2.5%	97.5%
Constant (beta)	.017	(.011)	−.004	.038
Constant (alpha)	−.173	(.013)	−.199	−.148
Random Effects				
Area Location Effect Variance	.089	(.005)	.079	.099
Area Scale Effect Variance	.119	(.008)	.104	.136
Location-Scale Covariance	−.048	(.005)	−.057	−.039
Location-Scale Correlation	−.466	—	—	—
ICC (Pop. Avg.)	.090	—	—	—
N of respondents		46,346		
DIC		125,443		

ABBREVIATIONS: DIC = Deviance Information Criterion; ICC (Pop. Avg.) = intraclass correlation (population average); SD = standard deviation.

of the proportion of each ethnic group in the local area, as well as a quadratic term to allow for nonlinearity. In models 3 through 5, we fit conventional mixed-effects models to test our hypotheses regarding the relationship between CE consensus and residents’ worry about crime, risk avoidance behavior, and violent victimization experience. Linear, logit, and Poisson link functions are specified for each outcome, respectively. All models are estimated using Markov chain Monte Carlo (MCMC) methods as implemented in the Stat-JR statistics package (Charlton et al., 2013).

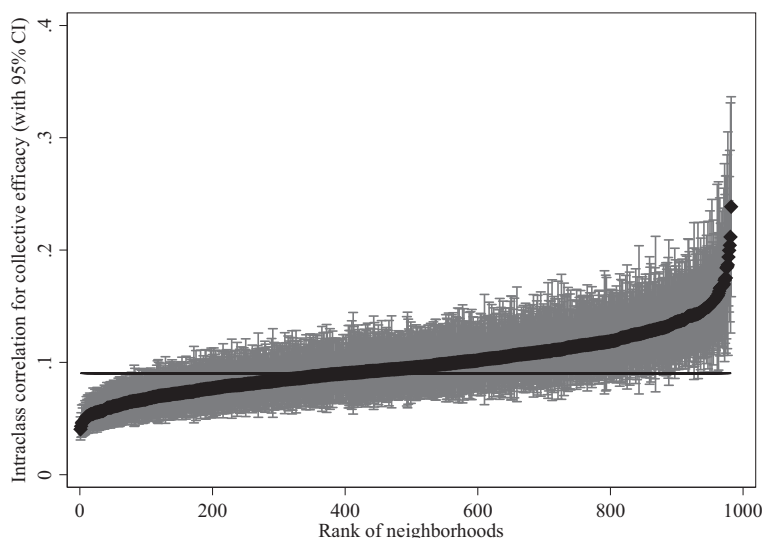
RESULTS

Model 1 (table 1) shows that most variability in CE ratings is between residents, with neighborhoods accounting for 9 percent of the total variance (ICC (Pop. Avg.) = .090). This falls in the middle of the range of estimates from previous studies, in which between 5 percent and 20 percent of the variation in CE is found to be situated at the neighborhood level (Raudenbush and Sampson, 1999).

The scale equation variance of .12 reveals that there are significant differences between neighborhoods in their level of CE consensus, mirroring the findings of Browning, Dirlam, and Boettner (2016) in Chicago and LA neighborhoods. The distribution of this between-neighborhood variability in CE consensus is presented graphically in figure 1, which plots the model estimated ICC for each of the 982 MSOAs in London, with 95 percent credible intervals (note that the higher the ICC, the smaller the neighborhood residual variance and therefore the higher the level of CE consensus). The figure shows that the MSOA ICCs vary considerably around the population-average ICC of .09 (indicated by the horizontal line), with 95 MSOAs (10 percent) having an ICC that is significantly lower than this London-wide average, and 132 MSOAs (13 percent) with an ICC significantly higher than this average. In short, CE is more “collective” in some neighborhoods than it is in others.

There is a moderate negative correlation (−.466) between the neighborhood location and scale random effects, such that areas with higher average CE also tend to exhibit more consensus about its extent in the local area. This covariance may, in part, be an artefact resulting from the response scales on which the CE indicator variables are measured creating “ceiling” effects (Brunton-Smith, Sturgis, and Leckie, 2017). As

Figure 1. Ranked Neighborhood ICC Presented with 95% Credible Intervals



NOTE: Horizontal line shows the mean of the ICCs across neighborhoods.

respondent ratings move from the top to the middle of the response scale, the mean by definition decreases, but the variance is also likely to increase because there are more response options available from which respondents can choose. This negative correlation may also arise substantively if neighborhoods that have high levels of CE are also richer in contextual cues and signifiers on which judgments are based, leading to a higher level of agreement between residents.

When we turn to model 2 in table 2, we see that the population average ICC has reduced to .069 with the addition of the individual- and neighborhood-level covariates. Although the fixed effects in the location equation are not our primary interest in this article, it is worth noting that ratings of CE are higher among older residents, Asians and Blacks, full-time workers, and longer term neighborhood residents. In contrast, single people, those in lower social class groups, and people in rented accommodations report lower levels of CE. At the neighborhood level, average CE is lower in more economically disadvantaged and more urban neighborhoods, and in neighborhoods that have a higher concentration of terraced housing and flats. The direction of these coefficients is consistent with existing studies (Mazerolle, Wickes, and McBroom, 2010; Sampson, Raudenbush, and Earls, 1997), although it is notable that ethnic minority groups have generally been found to report lower levels of perceived CE than Whites (Mennis, Dayanim, and Grunwald, 2013; Twigg, Taylor, and Mohan, 2010).

In the model 2 scale equation, individuals in higher social class groups, home owners, and full-time employees show higher levels of CE consensus, while women and single or divorced people have lower rates of agreement about the local level of CE (positive coefficients in the scale equation indicate characteristics associated with mover variable assessments and hence *lower* CE consensus). To give some sense of the substantive

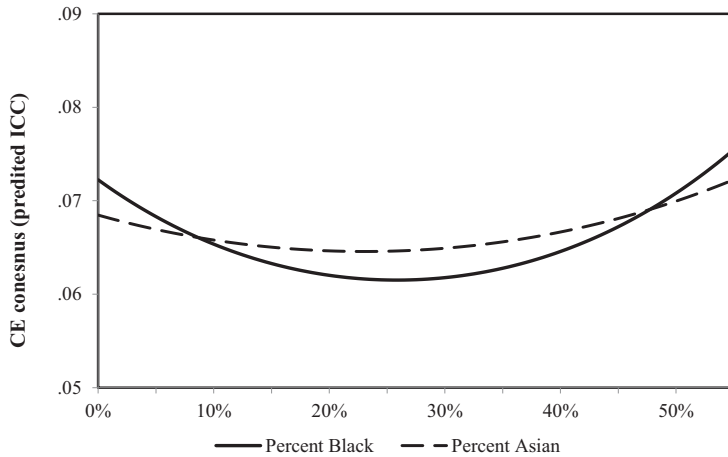
Table 2. Model 2: Mixed-Effects, Location-Scale Model With Covariates (Location and Scale)

Variables	Location Equation (Beta)				Scale Equation (Alpha)			
	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%
Constant	-.249	(.053)	-.357	-.145	-.279	(.066)	-.405	-.151
Female	.002	(.009)	-.015	.019	.040	(.015)	.011	.068
Age (centered)	.029	(.003)	.022	.036	.020	(.006)	.009	.031
Ethnicity (ref: White)								
Asian	.140	(.014)	.113	.166	-.085	(.023)	-.130	-.039
Black	.119	(.014)	.092	.146	-.092	(.023)	-.137	-.047
Mixed/other	.049	(.016)	.018	.079	-.083	(.026)	-.135	-.031
Marital Status (ref: Married)								
Single	-.079	(.012)	-.102	-.056	.149	(.019)	.111	.186
Widowed	-.044	(.018)	-.080	-.008	.023	(.028)	-.032	.078
Divorced/separated	-.180	(.019)	-.218	-.142	.202	(.029)	.146	.258
Social Class (ref: Class A/B)								
Class C	-.055	(.012)	-.079	-.031	.056	(.021)	.015	.098
Class D/E	-.043	(.016)	-.074	-.011	.114	(.026)	.062	.166
Tenure (ref: Privately Owned)								
Rented (social)	-.159	(.012)	-.182	-.135	.195	(.019)	.158	.232
Rented (private)	-.177	(.012)	-.201	-.154	-.015	(.021)	-.055	.025
Rented (other)	-.127	(.036)	-.197	-.056	.180	(.054)	.075	.288
Work Status (ref: Employed Full-Time)								
Part-time	-.060	(.016)	-.092	-.028	.099	(.027)	.047	.151
Student	-.018	(.021)	-.059	.022	-.078	(.036)	-.148	-.007
Not-working	-.074	(.012)	-.098	-.050	.115	(.020)	.077	.153
Neighborhood Measures								
Concentrated Disadvantage	-.157	(.019)	-.195	-.120	.029	(.027)	-.023	.081
Population Mobility	.002	(.013)	-.024	.029	-.042	(.018)	-.078	-.006
Urbanicity	-.063	(.011)	-.085	-.041	.008	(.016)	-.023	.038
Age Profile	.009	(.012)	-.015	.032	.020	(.017)	-.013	.051
Housing Structure	-.102	(.017)	-.135	-.070	.006	(.023)	-.038	.050
Proportion Asian	-.693	(.237)	-1.154	-.217	.544	(.325)	-.117	1.159
Proportion Asian ²	.987	(.415)	.156	1.799	-1.182	(.568)	-2.254	-.029
Proportion Black	-.674	(.381)	-1.427	.060	1.333	(.565)	.244	2.482
Proportion Black ²	1.816	(.834)	.204	3.464	-2.581	(1.232)	-5.012	-.137
Proportion Mixed/Other	13.329	(1.769)	9.704	16.852	-5.225	(2.236)	-10.062	-1.326
Proportion Mixed/Other ²	-71.117	(11.050)	-93.053	-48.200	15.188	(14.222)	-10.264	46.017
Cluster Size (centered)	-.002	(.000)	-.003	-.001	.002	(.001)	.001	.003
Random Effects								
Area Location Effect Variance	.058	(.004)	.052	.066				
Area Scale Effect Variance	.104	(.007)	.090	.119				
Location-Scale Covariance	-.030	(.004)	-.038	-.023				
Location-Scale Correlation	-.390	—	—	—				
ICC (Pop. Avg.)	.069	—	—	—				
N of respondents		46,346						
DIC		123,855						

ABBREVIATIONS: DIC = deviance information criterion; ICC (Pop. Avg.) = intraclass correlation (population average); SD = standard deviation.

magnitude of these differences, we can calculate population average within-area variances and associated ICCs (equation 4) for each characteristic, while holding all other variables at their mean (see table A3 in the appendix). This shows that, for example, CE consensus is approximately 11 percent higher for those in the highest social class group compared with those in the lowest (.071 vs. .064), 21 percent higher for married compared with

Figure 2. Percentage Residents from Black and Asian Backgrounds and Collective Efficacy Consensus



divorced people, and 20 percent higher for home owners compared with social renters (.070 vs. .059).

We find the same nonlinear relationship between immigrant concentration and CE consensus in London as Browning, Dirlam, and Boettner (2016) did for Latinos in Chicago and LA, with lower levels of CE consensus as the share of Black residents increases up to a threshold of approximately 30 percent, beyond which further increases in the proportion of Black residents increases CE consensus. The same pattern is evident for the proportion of Asian residents, although the estimates for the main effect coefficients are not significantly different from zero. These nonlinear relationships can be seen in figure 2, which plots the predicted neighborhood intraclass correlations from model 2 against the percentage of Black and Asian residents in the neighborhood.

Table 3 presents the key parameter estimates for the models predicting individual fear of crime, risk avoidance behavior, and experience of violent crime as a function of average levels of CE, CE consensus, and their interaction. Recall that these CE measures are derived as posterior estimates of the neighborhood location and scale random effects from model 1, such that a higher level of CE consensus is identified as an area with a *lower* predicted scale effect $\hat{u}_j^{[2]}$ (less variable CE ratings). To preserve space, we present only the fixed-effect coefficients for these parameters in table 3; the full set of parameter estimates for these models is included in the appendix (table A4).

We find support for hypotheses H1 and H3; the negative associations between average levels of CE and individual level fear of crime (model 3) and violent victimization experience (model 5) are significantly stronger in areas characterized by higher levels of CE consensus. CE consensus does not, however, moderate the effect of average CE on risk avoidance behavior, and the main effect of CE consensus in model 2 is significant and positive, however, suggesting that the level of CE consensus has an independent role in shaping residents' propensities to deliberately avoid certain parts of the neighborhood than mean levels of CE. We will return to a consideration of this unexpected result in the discussion.

These effects are presented graphically in figure 3, which plots the predicted score on

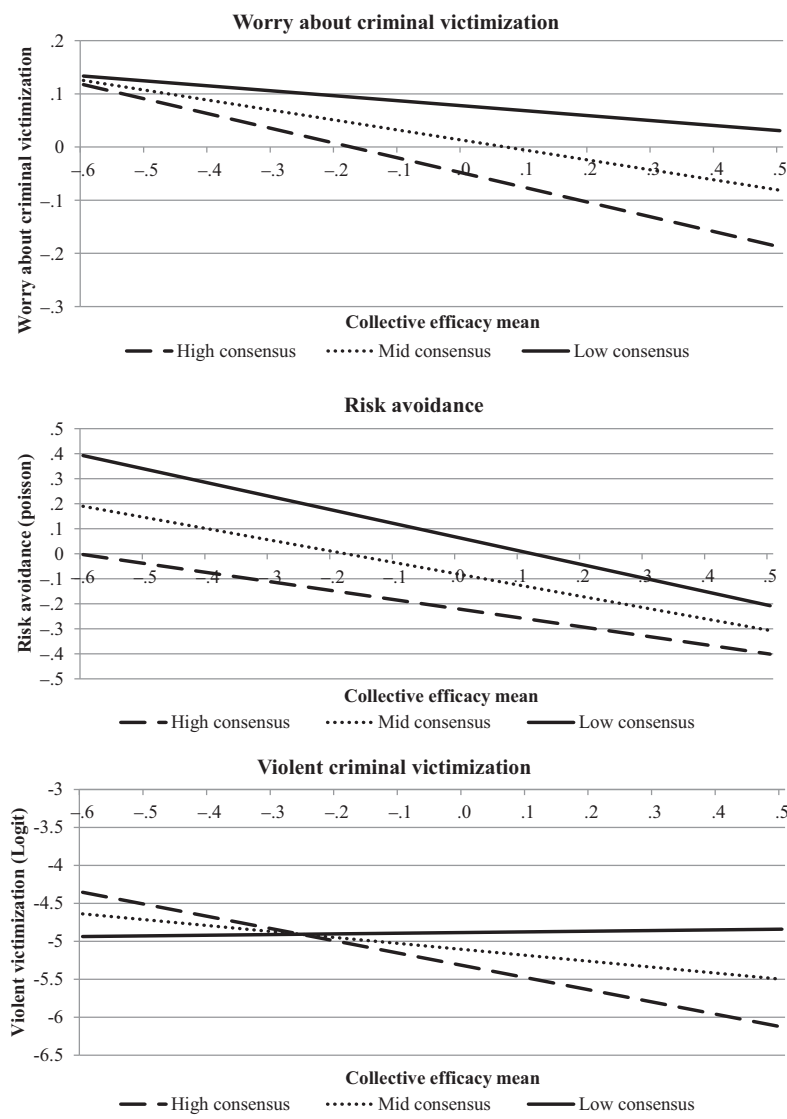
Table 3. Model 3–5 Results: Mixed-Effect Models Examining the Effect of CE Consensus (H1 to H3)

Variables	3. Worry About Crime (Linear)			4. Risk Avoidance (Poisson)			5. Victim of Violent Crime (Logit)					
	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%
Constant	-.049	(.062)	-.165	.078	-.143	(.110)	-.314	.105	-4.956	(.541)	-6.019	-3.924
CE (Mean)	-.190	(.052)	-.291	-.084	-.449	(.091)	-.619	-.275	-.801	(.475)	-1.718	.129
CE (Variance)	.203	(.044)	.119	.289	.457	(.082)	.300	.612	.701	(.355)	.001	1.393
CE (Mean*Variance)	.295	(.116)	.066	.522	-.294	(.213)	-.686	.119	2.723	(1.286)	.339	5.353
Random Effects												
Area Variance	.079	(.005)	.071	.089	.302	(.020)	.266	.343	.196	(.127)	.043	.458
Residual Variance	.830	(.006)	.819	.841	—	—	—	—	—	—	—	—
N of Respondents	46,346				28,420					16,021		
DIC	123,688				90,564					1,709		

NOTES: To preserve space, we present only the fixed effect coefficients for CE mean, CE variance, and their interaction. The full set of parameter estimates is included in table A4 of the appendix.

ABBREVIATIONS: CE = collective efficacy; DIC = deviance information criterion; SD = standard deviation.

Figure 3. How Worry, Risk Avoidance, and Criminal Victimization Varies as a Function of Collective Efficacy Mean and Consensus



each outcome as a function of mean CE, by terciles of CE consensus. Expressed worry about crime (top panel) declines as the mean level of neighborhood CE increases at all levels of CE consensus, but the rate of decrease is greater the higher the level of CE consensus. The same interaction is evident for violent victimization experience (bottom panel), although within the lowest tercile of CE consensus there is no association between the mean level of CE and the probability of having been a victim of violent crime. It is

notable that the moderating effect of CE consensus is greater at high average levels of CE, which is to say that residents do not provide substantially lower ratings of CE when there is a high degree of consensus about this judgment, compared with when consensus is low. The moderating effect of CE consensus appears, then, to be asymmetric in that its effect is greatest at high average levels of CE, although caution must be exercised in drawing this conclusion, based as it is on only two out of the three items that have been considered here.

DISCUSSION

A key feature of the theory of collective efficacy is that it relates to individuals' beliefs about the attitudes and likely behavior of other neighborhood residents. It concerns, fundamentally, what people believe other residents think and how they are likely to act in different situations and contexts (Sampson, 2012). This inherently social-psychological orientation implies that, for a variety of reasons, residents will differ in the judgments they make about CE and there will most likely be variability in the level of consensus about CE across neighborhoods. Existing research into the causes and consequences of CE has been focused almost entirely on neighborhood differences in average levels of CE, with little attention paid to the potential substantive importance of heterogeneity in the degree of agreement in these collective judgments. Our objective in this article has been to address this gap in understanding by investigating whether variability in CE consensus across local areas is consequential for residents' crime-related attitudes, behaviors, and experiences.

Using a mixed-effects, location-scale model (Hedeker, Mermelstein, and Demirtas, 2008), our findings show that heterogeneity in CE consensus in London is related to the ethnic composition of neighborhoods. When the share of Black residents in a neighborhood is low, CE consensus decreases as Black concentration increases. But when the total share of Black residents moves beyond a threshold of approximately 30 percent, further increases in Black concentration are associated with higher levels of CE consensus. The same nonlinear association was also evident for the proportion of Asian residents, although the effect was weaker and was not statistically significant. Our findings mirror those of Browning, Dirlam, and Boettner (2016), who observed the same nonlinear relationship for Latino concentration in Chicago and LA neighborhoods. These authors attributed this effect to a convergence of neighborhood narrative frames (Small, 2004), which occurs as the immigrant concentration reaches a threshold. This threshold represents an inflection point at which the result of further increases in ethnic concentration change from processes of social disorganization (Putnam, 2007) to "immigrant revitalization" (Browning and Soller, 2014; Kubrin and Desmond, 2015), such that further increases in ethnic concentration increase community cohesion, trust, and shared beliefs about willingness to intervene. Our results support this conclusion by replicating the nonlinear association in a new context, London, which, though different in important ways to Chicago and LA, also shares many of the same ethno-racial social and economic inequalities as well as a notable vitality in many ethnically diverse local communities.

The key contribution of this study has been to assess, for the first time, whether variability in the consensus of judgments is related to the sorts of crime-related outcomes that CE has been posited to influence (Brunton-Smith, Sutherland, and Jackson, 2014; Farrall, Jackson, and Gray, 2009; Nix et al., 2015; Sampson, Raundenbush, and Earls,

1997; Sampson, 2009). An essential feature of Sampson's conception of CE is that it relates to residents' beliefs about the likely attitudes and behavior of other people in the neighborhood. It follows from this that in neighborhoods where CE consensus is low, residents' ability to make inferences of this nature will be impeded. In line with this theoretical expectation, we found that CE consensus in London neighborhoods moderates the association between average levels of CE and both worry about crime and experience of violent victimization. In neighborhoods with low levels of CE consensus, the association between average levels of CE and these outcomes are close to zero. This, we contend, is because when the signs and signals of social cohesion, trust, and willingness to intervene are "noisy," the protective effects of higher average levels of CE in a local area are diminished. When CE signifiers are "clearer," residents will be more confident that others will intervene, or support their own interventions in threatening situations, increasing the pool of capable guardians, which in turn reduces the frequency of situations where motivated offenders encounter unprotected targets (Cohen and Felson, 1979; Reynald, 2011). This moderating effect of consensus may explain some of the mixed findings in the existing literature on the relationship between CE on levels of crime and anti-social behavior, as in none of these studies was variability in CE consensus across areas taken into account (Browning, 2009; Hipp and Wickes, 2017; Sutherland, Brunton-Smith, and Jackson, 2013; Villarreal and Silva, 2006; Wickes et al., 2017).

We did not find a moderating effect of CE consensus for the model predicting risk avoidance behavior, although the main effect of CE consensus was significant, such that residents were more likely to report avoiding certain places in the neighborhood when CE consensus was low. Therefore, CE consensus may have a direct influence on some crime-related outcomes, in addition to its moderating influence on average levels of CE. It is possible that this arises because an inability to assess the level of CE reliably in a neighborhood can itself serve as a source of crime-related anxiety for residents. Evolutionary biologists have long known that humans and other animals use environmental cues to assess the probability of danger and to respond appropriately through the "fight or flight" response of the sympathetic nervous system (Cannon, 1932). Crucially, it is not only obviously threatening cues, such as signs of predators, that result in acute stress, but also *ambiguity* in environmental cues can induce the "fight or flight" response because an inability to assess the level of threat as a result of ambiguity of available stimuli is anxiety provoking in its own right (Nader and Balleine, 2007; Tsetsenis et al., 2007). This is of course somewhat speculative and based on a single outcome in one location, but it nevertheless suggests ways in which research into the consequences of CE consensus might be extended in future studies.

This study is not without limitations. First, it is possible that some variability between areas that we attribute to differences in CE consensus between residents may in part reflect differential measurement error arising from survey interviewers. Brunton-Smith, Sturgis, and Leckie (2017) found substantial within-interviewer heterogeneity in survey responses in face-to-face interviews, suggesting interviewers are an important source of survey outcome variance (see also Davis and Scott, 1995; Mangione, Fowler, and Louis, 1992; Schnell and Kreuter, 2005; West, Kreuter, and Jaenichen, 2013). This may, in turn, attenuate the moderating effect of CE consensus on worry about victimization, risk avoidance, and victimization experience. Given that our choice of neighborhood boundaries, however, is not coterminous with interviewer assignments on the METPAS survey, we believe the potential risk of contaminating effects of interviewers to be minimal.

Unfortunately, we cannot reject this possibility definitively because we could not obtain the interviewer identifiers in the data.

Second, a note of caution is warranted regarding the interpretation of these relationships as causal effects, given our reliance on cross-sectional data. Sharkey, Torrats-Espinosa, and Delaram Takyar (2017) showed that because community organizations are often formed *in response to* high rates of violent crime, the findings from cross-sectional analysis will tend to show a positive correlation between concentration of community organizations and crime rates, when the causal effect is negative. Similarly, the relationship between ethnic minority concentration and CE consensus may arise, at least in part, as a result of residential sorting, with people who select into homogenously White areas being more likely to possess the sorts of characteristics associated with providing more variable assessments of CE in their neighborhood (Abascal and Baldassari, 2015). This alternative explanation is supported by the fact that, in addition to the association with Black and Asian concentration, we also found CE consensus to be lower among lower status groups in society such as social renters, lower skilled and manual occupations, divorcees, and women. In research into neighborhood social capital and generalized trust, scholars have found a similar pattern of associations with demographic variables and have pointed to the denser and deeper social networks and informal ties of higher status groups as the explanatory mechanism (Hooghe and Stolle, 2003; Putnam, 2000). These kinds of social network effects may also produce greater CE consensus among social and economically advantaged groups as information on the likely actions of others is more easily communicated between residents within denser social networks (Hipp, 2016; Sampson, Raudenbush, and Earls, 1997). Be that as it may, the research design we have used here provides little leverage on the causes of these between-group differences and future research could usefully be aimed at addressing the mechanisms driving the associations between resident- and neighborhood-level characteristics and CE consensus.

While acknowledging these caveats, our findings nonetheless add to a growing understanding in criminology of how structural features of local areas seem to influence crime and disorder *indirectly*, through social-psychological filters of cognition, judgment, and affect (Mazerolle, Wickes, and McBroom, 2010; Mennis, Dayanim, and Grunwald, 2013; Sampson, Raudenbush, and Earls, 1997; Zhang, Messner, and Liu, 2007). We have shown that, for a fuller account of how CE functions in local environments, it is necessary to consider not only the average but also the variability across individuals and neighborhoods in these assessments. That the level of consensus in these kinds of judgments about collective community resources seems to play a key role in shaping the patterning of crime and disorder adds an important new perspective to neighborhood research. Much, however, remains to be understood about the causes and consequences of CE consensus, including other structural features of local environments, the generality of these findings in other national and international contexts, and to other indicators of crime and disorder. These, we contend, represent useful avenues for future research.

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APPENDIX

Table A1. Factor Loadings for Collective Efficacy and Worry About Crime

Variables	Factor Loadings
Collective Efficacy	
People in this neighborhood can be trusted	.735
People act with courtesy to each other in public spaces in this area	.733
You can see from the public space here in the area that people take pride in their environment	.706
If any of the children or young people around here are causing trouble, local people will tell them off	.729
The people who live here can be relied upon to call the police if someone is acting suspiciously	.707
If I sensed trouble whilst in this area, I could get help from people who live here	.572
Eigenvalue	2.932
Worry About Crime	
How worried are you about having your home broken into and something stolen?	.691
How worried are you about being mugged or robbed in this area?	.774
How worried are you about being insulted or pestered by anybody whilst in the street	.896
How worried are you about being physically attacked by a stranger in the street in this area?	.842
Eigenvalue	2.589

Table A2. Factor Loadings for Neighborhood Factorial Ecology

Variables	Concentrated Disadvantage	Urbanicity	Population Mobility	Age Profile	Housing Profile
Working Population on Income Support	.890	.245	.191	.138	.092
Lone Parent Families	.847	.222	.002	.263	.153
Local Authority Housing	.846	.064	-.009	.146	-.168
Working Population Unemployed	.843	.293	.173	.118	.125
Non-Car-Ownning Households	.798	.417	.363	-.010	.057
Working in Professional/Managerial Role	-.787	.002	.153	.146	-.368
Owner-Occupied Housing	-.608	-.249	-.349	-.572	.053
Domestic Property	.104	.921	.165	.052	.112
Green Space	-.214	-.902	-.180	-.011	-.043
Population Density (per Square KM)	.245	.824	.262	.150	-.135
Working in Agriculture	-.126	-.663	-.006	-.183	-.030
In Migration	-.074	.102	.916	.069	.071
Out Migration	-.019	.162	.903	.119	.134
Single Person, Non-Pensioner Households	.355	.364	.743	.134	-.092
Commercial Property	.378	.432	.529	.019	-.093
More than 1.5 People Per Room	.428	.472	.507	.197	-.326
Resident Population Older than 65	-.052	-.210	-.271	-.892	-.021
Resident Population Younger than 16	.427	.040	-.464	.635	.190
Terraced Housing	.323	.263	.102	.274	.689
Vacant Property	.319	-.118	.485	-.173	.530
Flats	.453	.359	.489	.008	-.524
Eigenvalue	9.292	3.270	1.904	1.426	1.275

Table A3. Variance Estimates and Predicted ICC

Variable	Variance Estimate	ICC
Population Average	.778	.069
Male	.794	.068
Female	.826	.066
Age (25%)	.784	.069
Age (75%)	.832	.065
Ethnicity (ref: White)	.834	.065
Asian	.766	.070
Black	.760	.071
Mixed/other	.767	.070
Marital Status (ref: Married)	.769	.070
Single	.892	.061
Widowed	.787	.069
Divorced/separated	.941	.058
Social class (ref: Class A/B)	.761	.071
Class C	.805	.067
Class D/E	.853	.064
Tenure (ref: Privately Owned)	.766	.070
Rented (social)	.931	.059
Rented (private)	.755	.071
Rented (other)	.917	.059
Work Status (ref: Employed Full Time)	.772	.070
Part time	.852	.064
Student	.713	.075
Not-working	.866	.063
Neighborhood Measures		
Concentrated Disadvantage (25%)	.792	.068
Concentrated Disadvantage (75%)	.826	.066
Population Mobility (25%)	.838	.065
Population Mobility (75%)	.790	.068
Urbanicity (25%)	.807	.067
Urbanicity (75%)	.814	.066
Age Profile (25%)	.802	.067
Age Profile (75%)	.821	.066
Housing Structure (25%)	.808	.067
Housing Structure (75%)	.814	.066

ABBREVIATION: ICC = intraclass correlation.

Table A4. Models 3–5 Full Results: Mixed-Effect Models Examining the Effect of CE Consensus (H1 to H3)

Variables	3. Worry About Crime (Linear)				4. Risk Avoidance (Poisson)				5. Victim of Violent Crime (Logit)			
	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%
Constant	-.049	(.062)	-.165	.078	-.143	(.110)	-.314	.105	-4.956	(.541)	-6.019	-3.924
Female	.230	(.009)	.213	.248	.312	(.012)	.288	.336	-.281	(.168)	-.614	.051
Age (centered)	.011	(.004)	.004	.018	.024	(.005)	.015	.033	-.205	(.062)	-.327	-.083
Ethnicity (ref: White)												
Asian	.148	(.014)	.120	.176	.212	(.019)	.174	.249	-.043	(.256)	-.557	.440
Black	.007	(.014)	-.021	.035	-.109	(.021)	-.150	-.067	-.202	(.258)	-.718	.282
Mixed/other	.020	(.016)	-.013	.052	.059	(.022)	.018	.102	.231	(.268)	-.311	.740
Marital Status (ref: Married)												
Single	-.049	(.012)	-.072	-.025	-.014	(.016)	-.046	.018	.366	(.209)	-.056	.776
Widowed	-.107	(.017)	-.142	-.073	.104	(.021)	.062	.144	-.040	(.441)	-.953	.782
Divorced/separated	.037	(.018)	.001	.072	.130	(.021)	.089	.171	.694	(.305)	.078	1.274
Social Class (ref: Class A/B)												
Class C	.032	(.013)	.007	.058	-.049	(.017)	-.082	-.015	.351	(.283)	-.178	.938
Class D/E	.055	(.016)	.023	.086	-.028	(.021)	-.068	.014	.503	(.342)	-.149	1.197
Tenure (ref: Privately Owned)												
Rented (social)	-.016	(.012)	-.039	.007	-.014	(.016)	-.044	.018	.027	(.207)	-.383	.425
Rented (private)	-.157	(.013)	-.182	-.131	-.049	(.017)	-.083	-.015	-.899	(.268)	-1.436	-.389
Rented (other)	-.101	(.034)	-.167	-.034	.100	(.042)	.018	.182	-.831	(.657)	-2.291	.296
Work Status (ref: Employed Full Time)												
Part time	.015	(.016)	-.018	.047	.264	(.020)	.224	.305	.383	(.250)	-.118	.860
Student	-.109	(.022)	-.152	-.065	.144	(.030)	.084	.203	-.230	(.335)	-.911	.399
Not-working	-.019	(.012)	-.043	.006	.178	(.016)	.147	.209	.121	(.240)	-.340	.595
Neighborhood Measures												
Concentrated Disadvantage	.085	(.023)	.041	.129	-.084	(.041)	-.157	-.001	-.403	(.201)	-.810	-.019
Population Mobility	.012	(.015)	-.018	.041	-.024	(.026)	-.074	.028	.021	(.134)	-.241	.280
Urbanicity	.043	(.013)	.018	.068	-.029	(.022)	-.075	.012	.008	(.106)	-.200	.218

(Continued)

Table A4. Continued

Variables	3. Worry About Crime (Linear)				4. Risk Avoidance (Poisson)				5. Victim of Violent Crime (Logit)			
	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%	Mean	(SD)	2.5%	97.5%
Age Profile	.006	(.014)	-.020	.032	.011	(.024)	-.037	.058	.006	(.114)	-.218	.224
Housing Structure	.028	(.018)	-.009	.064	-.123	(.036)	-.193	-.052	-.360	(.165)	-.687	-.042
Proportion Asian	2.111	(.267)	1.587	2.642	.611	(.465)	-.330	1.391	-.654	(2.148)	-4.666	3.739
Proportion Asian ²	-2.103	(.472)	-3.043	-1.194	-.208	(.790)	-1.591	1.363	1.342	(3.767)	-6.440	8.279
Proportion Black	-.679	(.482)	-1.623	.271	.436	(.664)	-.721	1.898	14.055	(3.733)	7.031	21.687
Proportion Black ²	.407	(1.022)	-1.598	2.386	-.513	(1.460)	-3.425	2.227	-26.656	(8.788)	-44.487	-10.421
Proportion Mixed/Other	-4.754	(2.183)	-9.623	-.810	-6.537	(3.543)	-13.320	-.865	-30.769	(15.502)	-58.546	-2.053
Proportion Mixed/Other ²	27.443	(13.374)	3.781	56.960	21.448	(22.269)	-16.797	63.655	138.969	(94.557)	-43.422	305.964
Cluster Size (Centered)	-.003	(.001)	-.004	-.002	.005	(.001)	.003	.008	-.007	(.005)	-.017	.003
Individual CE Rating ^a	-.194	(.005)	-.203	-.185	-.290	(.005)	-.300	-.280	-.562	(.072)	-.700	-.421
CE (Mean)	-.190	(.052)	-.291	-.084	-.449	(.091)	-.619	-.275	-.801	(.475)	-1.718	.129
CE (Variance)	.203	(.044)	.119	.289	.457	(.082)	.300	.612	.701	(.355)	.001	1.393
CE (Mean × Variance)	.295	(.116)	.066	.522	-.294	(.213)	-.686	.119	2.723	(1.286)	.339	5.353
Random Effects												
Area Variance	.079	(.005)	.071	.089	.302	(.020)	.266	.343	.196	(.127)	.043	.458
Residual Variance	.830	(.006)	.819	.841	—	—	—	—	—	—	—	—
N of Respondents	46,346				28,420				—	16,021		
DIC	12,3688				90,564				—	1m709		

ABBREVIATIONS: CE = collective efficacy; DIC = deviance information criterion; SD = standard deviation.
*Individual CE rating is group mean centered.